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The Analysis of Remote Vital Signs and Health Condition Monitoring by Integrating Wearable Medical Devices and Mobile Phones

Chenxi Yang[1,a,*]

[1]*Jinling High School Hexi Campus, Nanjing, Jiangsu Province, 210019, China*
a. 13913860398@163.com
**corresponding author*

Abstract: In recent years, the number of patients with chronic diseases has been steadily increasing. Among these conditions, some require real-time monitoring systems to track vital signs and ensure timely interventions in critical situations. However, many patients with chronic diseases are elderly and may live alone, making it difficult for them to receive immediate medical attention. This delay has resulted in numerous families losing their loved ones. Since 2020, wearable medical monitoring devices have experienced rapid development. These devices provide an effective solution for remotely monitoring patients while alleviating the burden on healthcare systems. This study reviews authoritative reports, surveys, and research articles to first explore various sensors used for monitoring vital signs, as well as data processing architectures and transmission methods, including their integration with smartphones. By utilizing wearable remote medical monitoring devices, the response time for patients to receive medical assistance in emergencies can be significantly reduced. Furthermore, these devices can also provide timely intervention during unexpected medical incidents in daily life, helping to prevent tragedies. However, analysis reveals that further optimization is needed for both the sensors themselves and the overall system. In particular, there is a need for in-depth research into optimizing algorithm architectures to balance real-time responsiveness and energy efficiency in data transmission. Additionally, the large-scale application of these devices in societal and clinical settings remains insufficient, requiring further experimental efforts to address these challenges.

Keywords: Health condition monitoring, Remote vital signs, Sensors, Wearable medical device, Mobile phone

1. Introduction

Since the emergence of multi-parameter vital sign monitoring systems in the 1960s, these systems have played a pivotal role in clinical environments such as hospital wards, intensive care units (ICUs), and operating rooms. By providing intuitive and real-time monitoring of patients' vital signs, they have greatly facilitated timely diagnoses and interventions by medical professionals. However, chronic disease patients frequently lack access to real-time medical monitoring during sudden health crises, resulting in delayed treatment and, in severe cases, life-threatening outcomes.

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With global development and the aging population becoming more pronounced, there is an increasing focus on personal and family health, driving the rapid advancement of wearable medical monitoring devices. Contemporary smart wearable devices, such as the Apple Watch, Galaxy Watch, and Huawei Watch D, have incorporated functionalities for measuring heart rate, blood oxygen saturation, respiratory rate during sleep, and body temperature. Despite these advancements, such devices primarily provide intermittent feedback on individual vital signs and are not suitable for real-time, continuous monitoring of patients' health conditions.

Current research has achieved preliminary results, including data models applicable to screening infectious disease patients and tracking their movements. Nonetheless, a comprehensive wearable monitoring system capable of real-time multi-parameter vital sign monitoring, akin to traditional clinical-grade monitoring systems, has yet to be developed. Furthermore, unresolved issues persist in the domains of secure data transmission and ethical data usage [1].

In particular, a complete system is urgently needed for scenarios requiring real-time monitoring of patients' activity levels and vital signs during rehabilitation after major illnesses, as well as for tracking the mental and physical states of individuals with severe psychiatric conditions.

This paper will explore and discuss emerging wearable sensors and their integration into wearable devices, alongside various data processing methodologies and health data transmission architectures, in Section II. Section III will examine the application of these systems across diverse pathological conditions, analyzing their advantages and potential benefits. Such systematic and real-time monitoring devices hold significant promise for ensuring timely medical intervention for chronic disease patients during acute events, thereby improving clinical outcomes and quality of life.

2. Introduction to the Sensor and Mobile Application Software

In multi-parameter monitoring, the selection of devices to acquire various vital sign data from patients is fundamental and remains a key focus in the industry. Wearable sensors offer a cost-effective, user-friendly, and minimally intrusive solution for remote medical monitoring and assessment. These devices can collect specific vital sign data, such as heart rate, blood oxygen levels, and blood glucose, often used for fitness and exercise analysis. Some companies have advanced these capabilities, incorporating innovative materials and implantable sensors to monitor vital signs, and transmitting data to smartphones for display and interaction through user interfaces [2]. The first part of this section provides a detailed analysis of wearable sensors, followed by an overview of smartphone applications for health monitoring. The final part explores sensor architectures integrating wearables with smartphones, emphasizing system construction.

2.1. Health Sensor Overview

2.1.1. Photoplethysmography (PPG) Sensor

Photoplethysmography (PPG) sensors utilize the principle of photoplethysmography, employing optical technology to non-invasively detect blood volume changes in human or other biological tissues through the skin. By emitting light onto the skin and monitoring the phase differences between transmitted and reflected light, PPG sensors capture variations in blood flow, which can then be used to calculate parameters such as blood flow velocity, heart rate, sleep state, and physical activity via algorithmic processing.

PPG sensors operate in two modes. The first, transmission mode, involves light passing through the skin and being detected by a sensor on the opposite side. This method is commonly used in fingertip pulse oximeters. The second, reflection mode, involves light being emitted onto the skin's surface, with a portion of the light reflected back to the photosensitive sensor by tissues such as skin, blood vessels, or nerves. Once the light penetrates the skin, it is absorbed or diffracted by various

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tissues. In the absence of intense physical activity, light absorption by tissues like muscles, bones, and veins remains relatively constant. However, the dynamic flow of blood alters its light absorption during each cardiac cycle.

PPG sensors convert light into electrical signals. The absorption by static tissues is represented as a DC (direct current) signal, while the varying absorption by arterial blood flow due to heartbeat is represented as an AC (alternating current) signal. By separating these signals, algorithms can derive heart rate and blood flow velocity from the AC signal.

Optical heart rate sensors in devices like the Apple Watch have advanced to the third generation, achieving up to 80% accuracy in heart rate monitoring during physical activity [3]. While PPG technology still faces challenges in tracking cardiac conditions, its significance for remote monitoring is substantial.

2.1.2. Heart Rate and ECG Sensor

Heart rate and heart rate variability (HRV) are fundamental vital signs that reflect users' physiological states. Heart rate monitoring during exercise provides insights into physical performance and overall health, while electrocardiograms (ECG) are crucial for diagnosing cardiac conditions, such as myocardial infarction, which often exhibit clear ECG indicators.

A study involving 80 cardiac rehabilitation patients assessed the accuracy of wearable heart rate monitors. During treadmill and cycling exercises, devices on both wrists were used to measure resting and steady-state heart rates (HR) at 3, 5, and 7 minutes. Across 2,546 successful measurements, chest strap sensors showed the smallest mean absolute error (<1 BPM) compared to multi-lead ECG, with a correlation coefficient of 0.99. Among wrist-based devices, the Apple Watch exhibited the highest agreement with ECG, though still less accurate than chest straps. The study also found that PPG-based sensors generally underestimated HR, with no significant accuracy differences related to wrist size, weight, gender, or skin tone [4].

For wearable ECG systems, prior research integrated sensors with IoT frameworks to address noise from baseline drift or muscle activity. By fusing multi-lead data and employing algorithms (e.g., Median RR, Best SQI, Best Bayes), studies demonstrated reduced noise and improved signal quality [3].

However, single-lead ECG devices, such as the Apple Watch, remain susceptible to baseline drift and motion artifacts, occasionally leading to false atrial fibrillation diagnoses in users with minor hand tremors. Enhancing wearable ECG devices with advanced algorithms could improve accuracy significantly.

2.1.3. Blood Pressure Sensors

According to the *WHO's 2023 Global Hypertension Report*, 31% of individuals aged 30-79 suffer from hypertension, with nearly one-third of younger individuals also affected. Poor lifestyle habits in younger populations contribute significantly to elevated blood pressure, which can lead to conditions such as atherosclerosis, stroke, and myocardial infarction. This trend highlights the growing importance of blood pressure monitoring, not only for patients with chronic cardiac conditions but also as a vital metric in daily life.

Among mass-produced wearable devices, the HUAWEI Watch D employs a cuff with a differential pressure sensor to measure blood pressure. It functions by detecting pressure changes during cuff inflation and deflation, enabling indirect blood pressure measurement. Combined with PPG technology, it can also provide continuous monitoring. Additionally, the device incorporates a Hall sensor to detect magnetic field variations, ensuring leakage prevention during inflation through an electromagnetic valve.

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Capacitive pressure sensors have further advanced wearable blood pressure monitoring. A 2021 study introduced a flexible sensor structure, incorporating a polydimethylsiloxane (PDMS) dielectric layer enriched with deionized water to enhance porosity, sandwiched between indium tin oxide-coated polyethylene terephthalate electrodes. This improved the sensor's performance, offering a wide pressure range from 1 Pa to 1 kPa and varying sensitivities: 1-5 Pa: 1.7×10^{-3} kPa^{-1}, 10-50 Pa: 0.068 kPa^{-1}, 100-500 Pa: 0.095 kPa^{-1}, 5-30 kPa: 1.4×10^{-3} kPa^{-1}.

The material demonstrated excellent repeatability and stability in testing. In practical applications, the sensor was placed between a cuff and a simulated arm model, with a Fluke non-invasive blood pressure analyzer applying pressure. The sensor's capacitive changes captured oscillometric waveforms, showing strong linearity within the blood pressure range (sensitivity: 2.92×10^{-4} $mmHg^{-1}$) and accurately distinguishing between hypotension, normal, and hypertension states. These findings represent a significant advancement in wearable blood pressure monitoring research [5].

2.1.4. Electroencephalography Sensors

As mentioned above, for patients with severe mental illnesses, such as depression, real-time monitoring is also necessary. Objective and timely diagnosis of depression is inseparable from EEG analysis. In past research, frontal EEG has revealed asymmetry in the alpha band among patients with depression, introducing more methods for assessing these patients. In recent studies, the wearable EEG headband product Dreem 3S from Beacon Biosignals has received FDA 510(k) clearance. This device uses six electrodes and an integrated accelerometer to collect clinical-grade EEG data in a home environment, providing up to 24 hours of continuous recording. This capability greatly facilitates the real-time monitoring of patients' mental states and does not require conductive gel, making it highly convenient to use. The mobile platform supports the quantification of sleep spindles, arousals, and other microstructures, and its database contains a large amount of clinical-grade EEG data, expanding research into neurodegenerative and mental disorders. Integrating such devices into comprehensive monitoring systems can provide timely warnings for patients with mental illnesses during episodes.

2.1.5. Positioning and Acceleration Sensors

For the elderly and patients recovering from major illnesses, positioning and acceleration sensors can promptly detect situations such as falls or fainting when mobility is impaired during the recovery process. Acceleration sensors can timely detect and issue warnings, combined with GPS positioning to accurately determine the location where an emergency occurs, enabling timely rescue. In past research, a low-power wearable system designed specifically for elderly individuals prone to falls has been developed. This system integrates accelerometer and gyroscope sensors and implements a convolutional neural network system on a programmable gate array. The sensor uses an ultra-low-power FPGA (iCE40UP5K) chip to process data collected by the sensor (LSM6DSOX IMU), which captures acceleration and orientation changes. It is equipped with a 6-axis IMU sensor to capture 3D acceleration and gyroscope data. The system comprehensively detects acceleration data, and when abnormal data is detected, it transmits the data to a shallow learning neural network for processing. Ultimately, the system was tested in a real-world environment with 51 participants, achieving an accuracy rate of 94.5% in software simulations and 83.5% after hardware deployment [6].

2.2. Sensor Materials and Power Consumption

The intrinsic properties of sensors significantly influence their usability, reliability, and convenience. Wearable sensors designed for real-world monitoring must exhibit excellent flexibility, lightweight construction, comfort, skin compatibility, and multifunctionality to minimize manufacturing costs.

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Recent studies have highlighted silk protein-based wearable sensors as promising candidates for health monitoring and therapeutic applications due to their natural biodegradability, high biocompatibility, and low manufacturing cost.

Silk protein, comprising fibroin and sericin, serves as the sensor's foundation. Fibroin offers exceptional mechanical properties and tunable degradation rates, while sericin functions as a stabilizer or adhesive, widely used in medical applications. These sensors can analyze various ions in body fluids to estimate blood glucose and blood gas levels. They also support temperature sensing for body temperature monitoring and can noninvasively record ECG and electromyographic signals. Additionally, silk-based sensors integrated with pressure sensors enable pulse and respiratory rate measurements. Beyond monitoring, these sensors have potential applications in artificial kidneys, drug delivery, and wound healing. However, challenges such as scaling up production for widespread application remain to be addressed [7].

Self-powered sensors are another emerging technology in medical monitoring. Recent advancements have demonstrated the integration of triboelectric nanogenerators (TENGs) into wearable sensors, enabling energy generation without traditional electromagnetic methods. This innovation supports energy-efficient and sustainable monitoring systems. For instance, combining electrospinning with silicone rubber coatings has achieved seamless integration of piezoelectric and triboelectric effects, significantly enhancing the output efficiency of nanogenerators [8].

2.3. Data Transmission Architecture and Mobile Software Adaptation

When integrating multiple sensors into a system, it is crucial to consider how the collected data can be transmitted to a visualization platform. Smartphone-embedded systems enable the development and adaptation of corresponding software, which can use real-time monitoring capabilities to transmit abnormal vital sign data promptly to hospitals or designated contacts, such as family members. A study published last year highlighted that current Internet of Things (IoT) technologies have been widely applied to wearable medical monitoring devices. These technologies overcome the limitations of traditional medical equipment, which cannot provide real-time or continuous monitoring.

As mentioned earlier, real-time medical monitoring demands low latency, high-volume data transmission and processing, as well as energy resource optimization to control power consumption and extend sensor lifespan. In this research, the authors proposed an energy-efficient healthcare data management method, leveraging IoT to improve vital sign monitoring efficiency and cloud computing to enhance data transmission. This system integrates multiple sensors as discussed earlier, enabling data collection via Bluetooth, Wi-Fi, and similar protocols, which are then uploaded to the cloud. The cloud preprocesses the data through denoising techniques and uses blockchain to optimize data storage and access. Abnormal data is flagged and placed into restricted states, while the system provides additional security measures.

This system achieved an accuracy rate of 97%, a sensitivity to abnormal data of 94%, and an overall system efficiency of 96%, significantly outperforming traditional methods. Furthermore, this technology reduced the total energy consumption of wearable sensor monitoring systems by 24%, making it a stable and reliable solution [9]. Integrating this system with smartphone-based health monitoring and alert software offers significant convenience for timely warnings and monitoring.

Additionally, embedding AI-trained models into smartphone applications can provide predictive insights into disease occurrence. In a recent study, researchers developed an AI-driven cardiovascular disease prediction model combined with IoT technology. They proposed a novel **Shuffled Frog Leaping-tuned Iterative Improved Adaptive Boosting (SF-IIAdaboost) algorithm, which collects real-time patient data through IoT devices. The collected data undergoes Z-score normalization for preprocessing and quality enhancement. Relevant features are extracted and used to train the model,

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enabling predictive analysis. The proposed SF-IIAdaboost algorithm, integrated with IoT device data, achieved a 95.37% accuracy rate, 94.3% sensitivity, 96.31% specificity, and 95.72% F-measure [10].

3. Situational Analysis

After the formation of the overall system, this section will provide a detailed analysis and explanation of certain real-life critical medical scenarios. The aim is to demonstrate, as intuitively as possible, the feedback and value of this system in practical applications.

3.1. Detection of Falls and Abnormal Vital Signs in Daily Life and Rehabilitation Process

Falls and injuries from falls can be extremely fatal for elderly individuals under certain circumstances. Osteoporosis, a common issue among the elderly, significantly reduces bone density and strength compared to younger individuals, making them more prone to fractures or bone cracks upon falling. Even more critically, falls can trigger life-threatening complications. Due to the weakened state of bones, a fall where the head strikes the ground may lead to insufficient protection of the brain by the skull, potentially causing cerebral hemorrhage or stroke, which can endanger life.

In such scenarios, the gravity acceleration sensor and GPS module mentioned earlier play a crucial role in detecting falls and promptly transmitting the location of the incident. When a fall occurs, the gravity acceleration sensor, through algorithms and anomaly data, detects the tilt or fall of the body. Simultaneously, the GPS sensor is activated to relay the fall event and its precise location to designated family members via the Internet of Things (IoT).

Additionally, various sensors monitoring vital signs are triggered to transmit real-time physiological data of the individual. For example, if the patient's heart rate rises significantly or their blood pressure exceeds the hypertension threshold of 140/90 mmHg, the smartphone interface prompts the patient to confirm symptoms such as numbness in one side of the body or slurred speech and actively monitors for signs of vomiting. If such symptoms are detected, the AI-trained model sends data to the hospital, indicating the likelihood of a stroke or other critical condition, enabling medical staff to prepare in advance for timely intervention.

In the context of major disease recovery, continuous monitoring is equally essential during in-hospital activities such as bedside movement. If a fall occurs during these activities, or if there are abnormal fluctuations in vital signs, the system must also provide immediate alerts to ensure rapid response and prevent further complications.

3.2. Acute Onset of Heart Disease and Chronic Disease

Cardiovascular diseases (CVDs) have become the leading cause of mortality worldwide. In 2019, an estimated 17.9 million people died from CVDs, accounting for 32% of all global deaths. Among these, 85% were due to heart attacks and strokes. Acute myocardial infarction (AMI) stands out as one of the most critical and fatal forms of heart disease. It occurs when plaque formation on the arterial walls reduces blood flow to the heart, leading to myocardial damage due to oxygen deprivation. Symptoms of myocardial infarction include chest pain (radiating from the left arm to the neck), shortness of breath, sweating, nausea, vomiting, abnormal heart rhythms, anxiety, fatigue, weakness, stress, depression, and other factors [11].

One of the most valuable applications of this system is in detecting and managing acute myocardial infarction. AMI patients often experience symptoms such as sweating, chest pain, rapid heart rate, chest tightness, and lowered blood pressure. The system continuously monitors the patient's heart rate and blood pressure during such events. If an increase in heart rate and a drop in blood pressure are detected, the ECG monitoring system is immediately activated to record a 12-lead electrocardiogram. If ST-segment elevation is observed, it may indicate occlusion of the left anterior

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descending coronary artery, leading to infarction in the anterior wall, apex, inferior wall, anterior septum, and the anterior papillary muscle of the mitral valve.

At this point, the mobile application prompts the patient to administer sublingual nitroglycerin while analyzing the abnormal data using the AI-trained model. The results are promptly and visually transmitted to the patient's family and the hospital through the Internet of Things (IoT). The system continuously updates the patient's status. In the case of severe malignant arrhythmias, such as ventricular fibrillation or ventricular tachycardia, the system will directly dial emergency services to ensure timely intervention.

This approach is also applicable to acute exacerbations of chronic diseases such as diabetes, cerebral infarction, hypertension, and pulmonary arterial hypertension. Patients can input their medical history during the initial system setup. In the event of an acute episode, the system monitors key physiological parameters and employs the AI model to detect abnormalities in vital signs, providing early warnings and facilitating prompt intervention.

3.3. Mental and Psychological State Monitoring

Unlike other conditions, mental illnesses are commonly observed among adolescents. According to WHO data from 2019, approximately 970 million individuals globally suffered from mental disorders, with anxiety and depression being the most prevalent. Adolescents accounted for a significant proportion of cases in certain specific mental health disorders. For illnesses like depression, where patients struggle to regulate their emotions, experience insomnia, and sometimes lose control over their behavior (e.g., self-harm or suicidal tendencies), the consequences can be tragically severe. Thus, monitoring mental health patients is as crucial as monitoring conditions such as coronary artery disease and hypertension.

Unlike acute conditions, mental health disorders require long-term monitoring. Initially, mental health patients may not need a fully integrated system; basic monitoring of metrics like heart rate and sleep patterns may suffice. If notable signs, such as significantly reduced sleep duration, are detected, the system can prompt the patient to report their recent mental state and recommend the activation of electroencephalogram (EEG) monitoring.

EEG often reveals distinctive patterns in mental health patients. For instance, individuals with schizophrenia may exhibit increased power in low-frequency bands (delta and theta waves) and reduced power in high-frequency bands (alpha, beta, and gamma waves). However, EEG-based assessments may not be universally applicable across all mental health disorders [12]. For specific patients, this system can provide real-time EEG monitoring to reflect their mental state. In cases of prolonged depressive episodes or other severe conditions, the system can notify family members or healthcare providers to enable timely intervention.

4. Conclusion

The integration of wearable vital sign monitoring systems represents a promising direction for future research in biomedical engineering. This paper explored the design of vital sign sensor systems and the overall processing architecture, followed by practical applications in real-life medical scenarios. Remote wearable medical monitoring systems can significantly reduce the time required for patients to receive medical intervention during critical episodes. Moreover, in daily life, these monitoring devices can provide timely assistance in unexpected health emergencies, potentially preventing tragedies.

However, the limitations of this study lie in the lack of a fully developed system, real-world simulations, and clinical or societal trials. Additionally, practical considerations such as energy

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consumption, operational ease, and optimization strategies were not thoroughly explored, highlighting areas for future in-depth research.

Further advancements are needed in sensor energy efficiency, stability, and material properties such as comfort and flexibility to ensure better integration into wearable systems. Additionally, optimizing algorithmic architectures and identifying solutions for balancing data transmission energy consumption with real-time responsiveness require more extensive investigation. These improvements will facilitate the widespread adoption of integrated wearable devices for remote medical monitoring, ultimately enhancing healthcare delivery and saving lives on a broader scale.

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